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The large influence of climate model bias on terrestrial carbon cycle simulations

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Abstract

Global vegetation models and terrestrial carbon cycle models are widely used for projecting the carbon balance of terrestrial ecosystems. Ensembles of such models show a large spread in carbon balance predictions, ranging from a large uptake to a release of carbon by the terrestrial biosphere, constituting a large uncertainty in the associated feedback to atmospheric CO₂ concentrations under global climate change. Errors and biases that may contribute to such uncertainty include ecosystem model structure, parameters and forcing by climate output from general circulation models (GCMs) or the atmospheric components of Earth system models (ESMs), e.g. as prepared for use in IPCC climate change assessments. The relative importance of these contributing factors to the overall uncertainty in carbon cycle projections is not well characterised. Here we investigate the role of climate model-derived biases by forcing a single global ecosystem-carbon cycle model, with original climate outputs from 15 ESMs and GCMs from the CMIP5 ensemble. We show that variation among the resulting ensemble of present and future carbon cycle simulations propagates from biases in annual means of temperature, precipitation and incoming shortwave radiation. Future changes in carbon pools, and thus land carbon sink trends, are also affected by climate biases, although to a smaller extent than the absolute size of carbon pools. Our results suggest that climate biases could be responsible for a considerable fraction of the large uncertainties in ESM simulations of land carbon fluxes and pools, amounting to about 40% of the range reported for ESMs. We conclude that climate bias-induced uncertainties must be decreased to make accurate coupled atmosphere-carbon cycle projections.

1. Introduction

By coupling the atmosphere, biosphere, hydrosphere and lithosphere, Earth system models (ESMs) aim to model an integrated Earth system with feedbacks and dependencies between physical, biological and biogeochemical dynamics at multiple scales. Biospheric and specifically terrestrial carbon cycle dynamics have been identified to be one of the largest contributors to overall uncertainties surrounding the magnitude of future climate change through biogeochemical feedbacks that affect atmospheric CO₂ concentrations (Meehl *et al* 2007). Benchmarking studies have pointed out a large spread between terrestrial carbon cycle simulations in ESMs used to characterise

biogeochemical feedbacks within the climate system (Anav *et al* 2013, Todd-Brown *et al* 2013, Jiang *et al* 2015). However, because of the close coupling between the state of the atmosphere and the processes (principally photosynthesis, soil organic matter decomposition and biomass burning) governing terrestrial carbon balance, such spread may be induced not only by parameters and process representations of the carbon cycle sub-model of the ESM, but also by the forcing climate as simulated by its atmospheric component (general circulation model, hereinafter GCM). This internally simulated climate forcing of the carbon cycle sub-model often contains substantial biases in comparison to historical climate records (Li *et al* 2013, Mehran *et al* 2014, Mueller and Seneviratne 2014).

Studies in which an offline ecosystem-carbon cycle model is forced with climate fields from multiple GCMs and ESMs generally show a large sensitivity of the simulated global terrestrial carbon balance to climate forcing (Berthelot *et al* 2005, Schaphoff *et al* 2006, Scholze *et al* 2006, Ahlström *et al* 2012, Ahlström *et al* 2013, Friend *et al* 2013, Ahlström *et al* 2015). Even when bias-corrected climate forcing data are used, i.e. where the biases as identified by comparison to observation-based climate datasets are subtracted from the raw GCM output (e.g. Ehret *et al* 2012, Hempel *et al* 2013), the uncertainty arising from differences in future trends between GCMs remains large (Ahlström *et al* 2013). This suggests that a similar effect may be present in ESM simulations, where the climate forcing of the carbon cycle sub-model is generated internally within the same model framework.

Here we force a single, non-coupled, global ecosystem-carbon cycle model with climate fields from GCMs and ESMs of the coupled model inter-comparison project phase 5 (CMIP5) (Taylor *et al* 2011) ensemble, to investigate the potential role of climate model-related biases (hereinafter ‘climate bias’) in projections of the terrestrial carbon cycle. To understand the role of annual and seasonal biases we applied the original (biased) climate, as well as annually and seasonally bias-corrected climate forcing. We analysed ensemble spread in simulated carbon pools and compared projected changes in carbon pools between the bias-corrected and non-bias-corrected forcing simulations, as well as the climate bias impacts on future carbon balance trends.

2. Method

2.1. Ecosystem-carbon cycle model

Historical and future carbon cycle response to forcing climate and CO₂ concentration were simulated with LPJ-GUESS (Smith *et al* 2001), an individual- and patch based dynamic vegetation-ecosystem model in which carbon cycle dynamics emerge as an outcome of simulated vegetation structure, demography and resource competition, soil carbon biogeochemical dynamics and biomass burning by natural wildfires. Vegetation is represented as a mixture of plant functional types (PFTs) (11 in this study; Ahlström *et al* 2012), distinguished by photosynthetic pathway (C₃ or C₄), life history strategy (shade tolerance), phenology (evergreen, summergreen or raingreen), growth form (trees or herbaceous plants) and bioclimatic distributional limits. Here we employed the model in cohort mode where age classes group individual plants within a number of replicate patches (10 in this study) in each grid cell.

Population dynamics (establishment and mortality) are influenced by current resource status, demography and the life-history characteristics of each PFT

(Hickler *et al* 2004, Wramneby *et al* 2008). Cohorts compete for resources and mortality occurs with low or negative growth efficiency, age, or following climatic change in violation to the PFT bioclimatic limits leading to biome shifts. Succession follows stochastic stand-clearing disturbance in each patch with a generic expectation of 0.01 yr⁻¹. In addition, fires are modelled prognostically based on temperature, current fuel load and moisture (Thonicke *et al* 2001). The detailed representation of demographics may improve simulations of carbon fluxes and pools (Purves and Pacala 2008, Fisher *et al* 2010, Wolf *et al* 2011, Haverd *et al* 2014).

We employed the carbon-only version 2.1 of LPJ-GUESS. A full description is available in Smith *et al* (2014) and references therein.

2.2. Forcing data and bias correction

2.2.1. Forcing data and experimental design

LPJ-GUESS was forced by outputs from 15 GCMs and ESMs (table 1) participating in the CMIP5 (Taylor *et al* 2011). These 15 models were selected as a representative sample that captures the spread in a larger ($n = 21$) ensemble of ESMs and GCMs. For all ESMs and GCMs, we used the realisations forced by prescribed CO₂ concentration following the representative concentration pathway 8.5 (Riahi *et al* 2007). All simulations were initialised with a 500 year spin-up to establish carbon pools in equilibrium with the initial forcing climate, using constant 1850 CO₂ concentrations and recycled de-trended 1850–1879 climate forcing fields. The initialisation was unique for each simulation, using climate fields from the corresponding transient simulation (original or bias corrected from the respective GCM/ESM) to ensure initial conditions in balance with the following transient simulations. Time-varying historical CO₂ concentrations and climate data from the respective GCM or ESM historical and future simulation were applied following the spin-up. We accounted for time-variant land use by prescribing grasses to the fraction of grid cells used as croplands and pastures in the LUH gridded land use database (Hurtt *et al* 2011).

2.2.2. Bias correction

Climate forcing fields were bias-corrected using 30 year (1961–1990) climatology based on gridded observations from CRU TS 3.0 as reference dataset (Mitchell and Jones 2005). Precipitation, downward shortwave radiation and air temperature from the ESMs and GCMs were bi-linearly interpolated to the CRU grid (0.5° × 0.5° resolution).

The interpolated fields were bias-corrected using the reference period 1961–1990, on annual and monthly basis (seasonal bias correction). The delta change approach was used to correct the temperature fields of the ESMs and GCMs (equation (1)),

Table 1. CMIP5 models and modelling groups used to analyse climate biases. Models highlighted in bold were used to force the land model simulations.

Modelling centre (or Group)	Institute ID	Model name
Canadian Centre for Climate Modelling and Analysis	CCCMA	CanESM2
National Center for Atmospheric Research	NCAR	CCSM4
Community Earth System Model Contributors	NSF-DOE-NCAR	CESM1-BGC
Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	CSIRO-QCCCE	CSIRO-Mk3.6.0
Centre National de Recherches Météorologiques/Centre Européen de Recherche et Formation Avancée en Calcul Scientifique	CNRM-CERFACS	CNRM-CM5
EC-EARTH consortium	EC-EARTH	EC-EARTH
LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University	LASG-CESS	FGOALS-g2
NOAA Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-CM3 GFDL-ESM2M
NASA Goddard Institute for Space Studies	NASA GISS	GISS-E2-R
Met Office Hadley Centre	MOHC	HadGEM2-CC HadGEM2-ES
Institute for Numerical Mathematics	INM	INM-CM4
Institut Pierre-Simon Laplace	IPSL	IPSL-CM5A-LR IPSL-CM5A-MR MIROC-ESM
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC	MIROC-ESM-CHEM MIROC5
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC	MIROC-ESM-CHEM MIROC5
Max Planck Institute for Meteorology	MPI-M	MPI-ESM-LR
Meteorological Research Institute	MRI	MRI-CGCM3
Norwegian Climate Centre	NCC	NorESM1-M

Table 2. Bias correction methods applied to climate forcing data.

Bias-correction method	Trends	Annual means	Seasonal variability	Inter-annual variability
No bias correction	ESM/GCM	ESM/GCM	ESM/GCM	ESM/GCM
Annual bias correction	Absolutely or relatively preserved from ESM/GCM	Corrected	Absolutely or relatively preserved from ESM/GCM	Absolutely or relatively preserved from ESM/GCM
Seasonal bias correction	Absolutely or relatively preserved from ESM/GCM	Corrected	Corrected	Absolutely or relatively preserved from ESM/GCM

$$T_t^{\text{corr}} = T_t^{\text{gcm}} - \overline{T^{\text{gcm}}} + \overline{T^{\text{ref}}}, \quad (1)$$

where T_t^{corr} is the bias-corrected temperature for month (t), T_t^{gcm} is the original temperature from the ESMs and GCMs, and $\overline{T^{\text{gcm}}}$ and $\overline{T^{\text{ref}}}$ are annual or monthly climatologies of the ESMs and the reference dataset, respectively. The climatologies represent 30 year annual averages (annual bias correction, $n = 1$) or monthly averages (seasonal bias correction, $n = 12$).

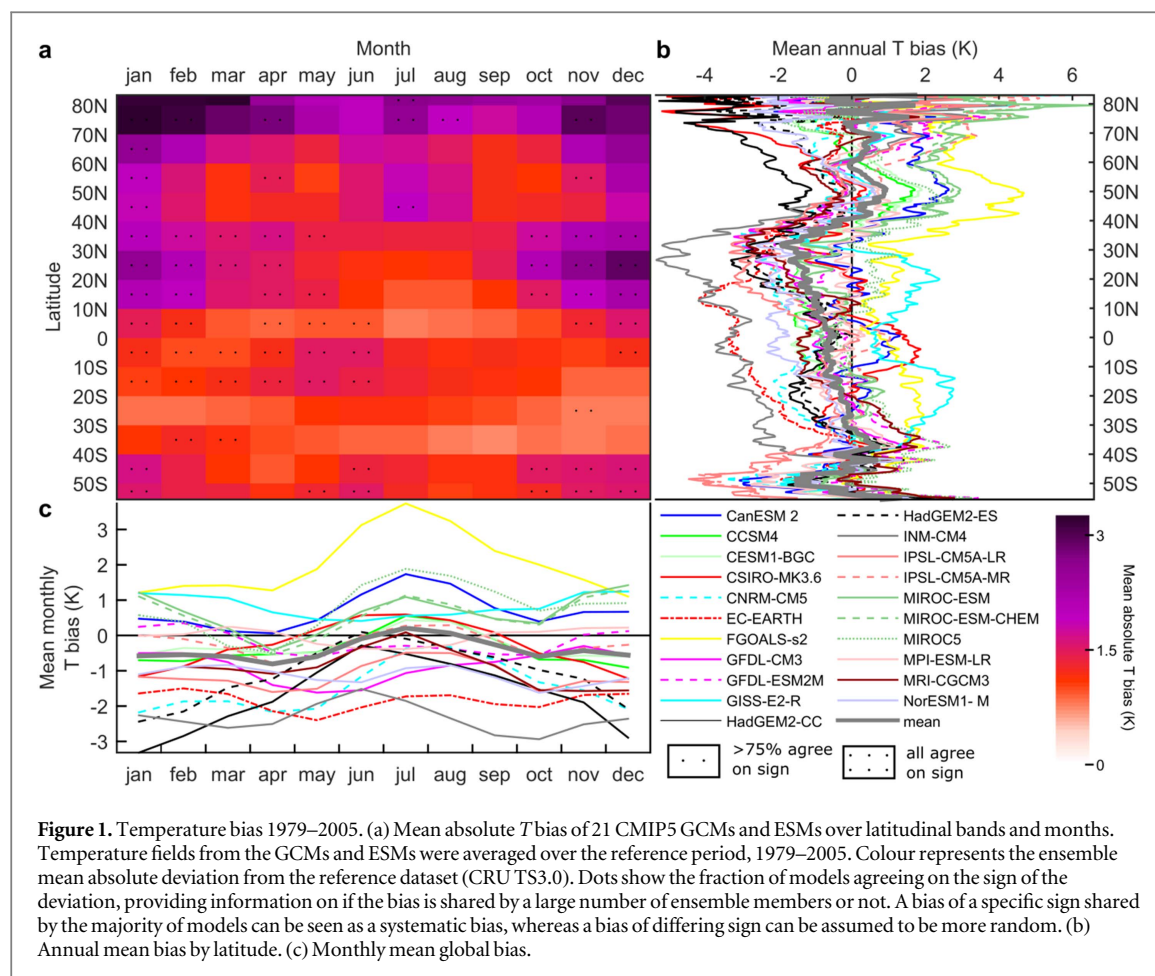
Precipitation and downward shortwave radiation were corrected using relative anomalies (equation (2)),

$$P_t^{\text{corr}} = \overline{P^{\text{ref}}} \times P_t^{\text{gcm}} / \overline{P^{\text{gcm}}}, \quad (2)$$

where P_t^{corr} is the bias corrected precipitation, P_t^{gcm} is the original ESM and GCM precipitation,

and $\overline{P^{\text{gcm}}}$ and $\overline{P^{\text{ref}}}$ are annual or monthly climatologies of the ESMs and reference dataset, respectively.

This implies that climate fields corrected by the annual bias correction method have identical 30-years grid cell means as the CRU climatology over the reference period 1961–1990, but potentially a different seasonal cycle, while both seasonal and annual biases were corrected in the seasonal bias correction method (table 2). None of the methods correct for variability on longer timescales (e.g. inter-annual, decadal or trends), which was absolutely (temperature) or relatively (precipitation and shortwave radiation) preserved relative to the original ESM or GCM simulation.



3. Results

3.1. Climate bias

Climate biases were evaluated over global ice free land. We analysed climate biases from a larger ensemble of models ($n = 21$) and present the corresponding simulations by LPJ-GUESS below where the ecosystem-carbon cycle model was forced by a smaller subset of these models ($n = 15$) that is representative of the full ensemble (table 1). Mean temperature biases between 1979 and 2005 are largest during winter at high latitudes, using temperature information from the climate research unit (CRU) TS3.0 station-based observational dataset as reference (Mitchell and Jones 2005). This is likely to be mainly a result of differences in sea ice extent in the models (figure 1). Models are relatively evenly distributed with both negative and positive biases around the reference dataset. There is little evidence of shared bias between models.

Precipitation biases show a different pattern compared to temperature biases, with large positive and negative biases in the tropics and a smaller but common positive biases in the northern extra-tropics (figure 2). CRU TS3.0 was used as reference climatology for the years 1979 through 2005. The generally shared positive biases in the southern hemisphere south of 40 °S (figure 2) mainly pertain to the southern

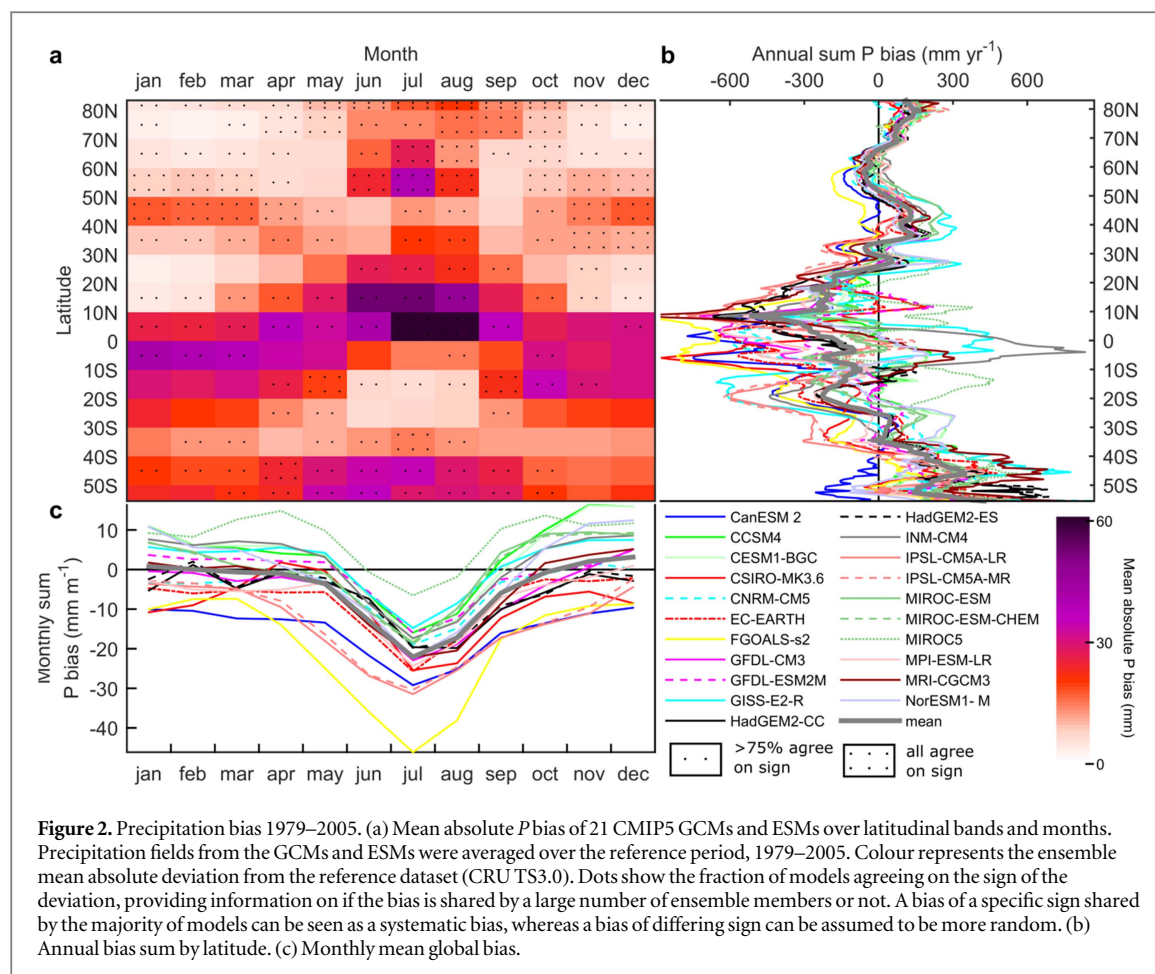
tip of South America, and thus a very limited land area. Due to the relatively coarse grid in the climate models compared to the observation data set, it is likely that the coastlines and land-sea separation are not well-resolved, which may explain a part of this shared bias.

Biases in downward shortwave radiation are overall substantial (figure 3). Uncertainties in shortwave radiation and the Earth energy budget have been previously discussed (Trenberth *et al* 2014) and reflect general uncertainties in radiation transfer, uncertain cloud cover and cloud morphology. Here we defined the reference climatology using surface downward shortwave radiation from the International Satellite Cloud Climatology Project (ISCCP; Schiffer and Rossow 1983, Zhang *et al* 2004) for the time period 1984–2000, bilinearly interpolated to 0.5×0.5 degree resolution.

Global observation-based datasets that are frequently used to force models also differ significantly, and the biases presented here are therefore dependent on the choice of reference dataset adding to the difficulties in estimating climate biases and removing their impact on Earth system simulations (Poulter *et al* 2011, Wu *et al* 2017).

3.2. Carbon cycle spread—the role of climate bias

The general spread in global ecosystem carbon when forcing LPJ-GUESS with raw, uncorrected, climate

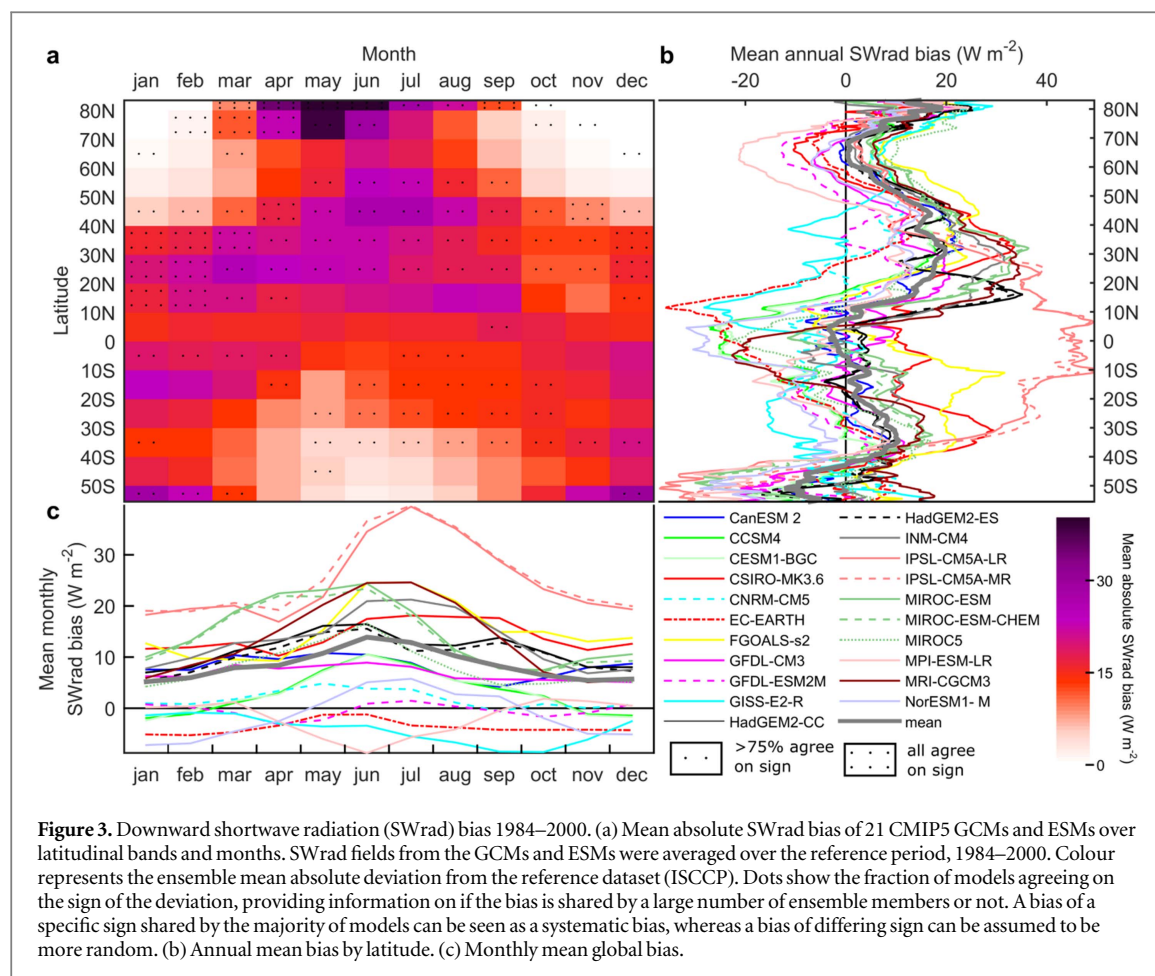


outputs from 15 CMIP5 GCMs and ESMs is large and relatively constant over time, from 1850 to 2100 (figure 4(a)). To quantify the spread we analysed the range (maximum minus minimum) and the inter quartile range (IQR, the difference between the 25th and 75th percentiles of the distribution). The range in simulated ecosystem carbon changes moderately over time from 987 Pg C for 1850–1879 to 953 Pg C for 1961–1990 and 1154 Pg C for 2071–2100. This difference between minimum and maximum ecosystem carbon, here induced solely by climate model biases, is about 40% of the range reported for 18 CMIP5 ESMs (Anav *et al* 2013). Moreover, the spread apparent for the hindcast part of the simulations is generally maintained in the future part; simulations showing relatively high or low carbon pools at 1850 generally do so at 2100 as well. Differences in trends since 1850 therefore have a much smaller impact on the ensemble spread at the end of the 21st century than the climate biases of the ESMs/GCMs. Correcting for annual biases reduces the range to about 40% of the original range and correcting for seasonal and annual biases causes a further reduction to about 20% of the original range (figures 4(b) and (c)). Annual correction accounts for an even larger reduction in the IQR; IQR decreases to ~30% of the original IQR, with smaller further reductions with the addition of seasonal correction (to ~20% of original IQR) suggesting that

the large impact of seasonal biases is represented by a smaller fraction of the ensemble ESMs and GCMs.

The results reveal a large impact of annual and seasonal climate-biases on simulations of the terrestrial carbon balance. The remaining spread, or uncertainty, is explained by variability on longer timescales than months, i.e. inter-annual and decadal variability. There is also a signal of increasing range and IQR backwards and forwards in time from the reference period of the bias correction, 1961–1990, indicating that differences in projected trends (from 1850 to reference period and from reference period to 2100) by the ESMs/GCMs are responsible for parts of this remaining spread. Partitioning the global ecosystem carbon spread to vegetation and soil carbon pools shows that soil carbon pools (including litter) are responsible for about 65% of the spread with the remainder associated with the vegetation pool (figures 4(d), (g)). The effect of correcting climate biases on vegetation and soil carbon pools is similar in relative magnitude (figures 4(d)–(i)).

Spatial evaluation reveals that the absolute climate bias effect on ecosystem carbon is largest in tropical rainforests, and cold-climate areas of the high northern latitudes and the Tibetan plateau (figure 5(a)). These regions have disproportionate significance in terms of the impact of climate bias on simulated ecosystem carbon balance. The reason is that these are



areas with relatively large carbon pools, either in vegetation (tropical forests) or in the soil (cold climate areas), which acts as a multiplier on the impact of climate bias on land-atmosphere carbon fluxes. When instead investigating the climate bias effect relative to the local ensemble mean ecosystem carbon, low productivity deserts and high latitudes stand out, but the Amazon basin also shows significant climate bias effect relative to the ensemble mean ecosystem carbon stock (figure 5(b)).

3.3. Changes in carbon uptake

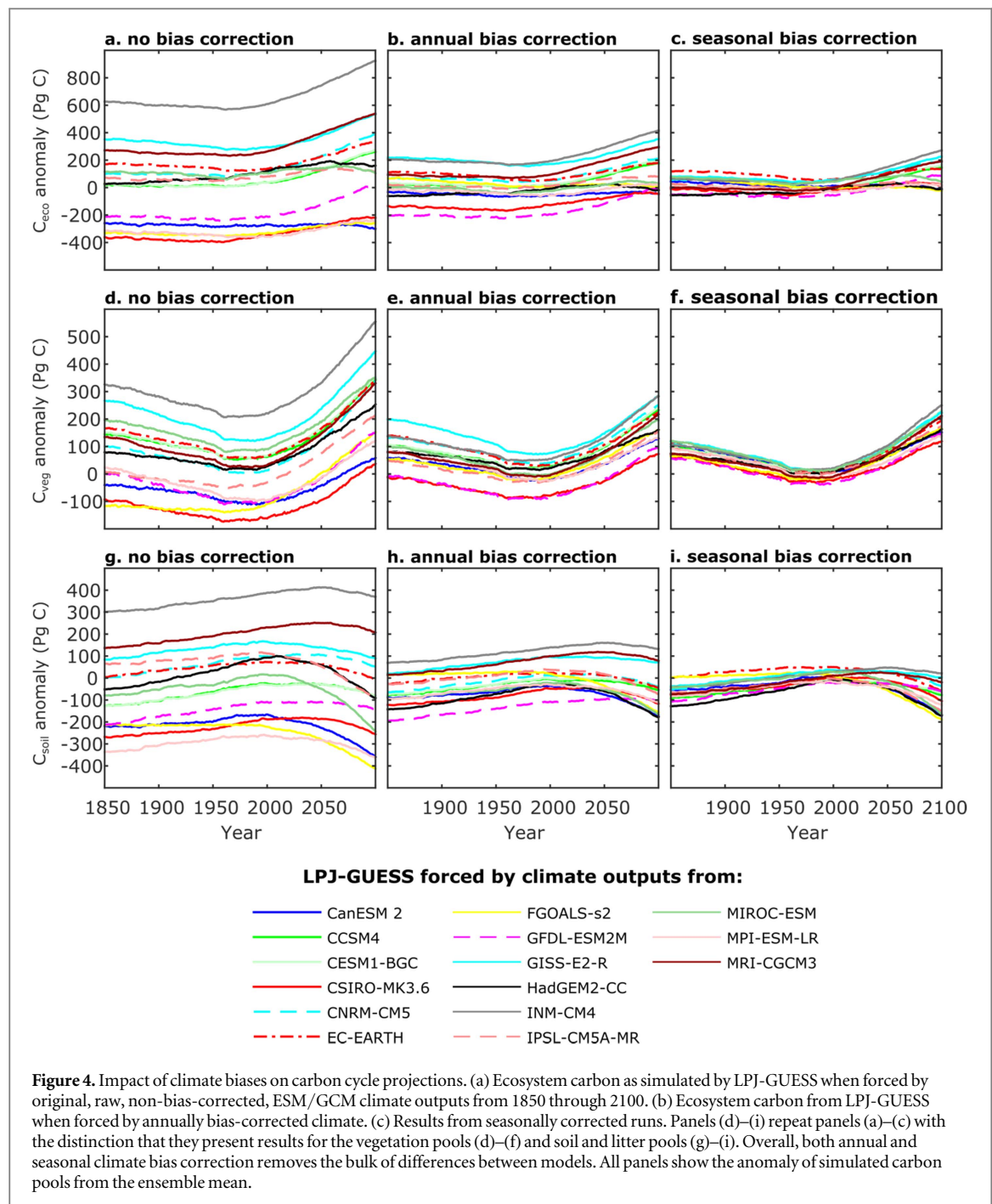
Having identified a large impact of climatic biases on simulated carbon pools, we evaluated if the simulated global future changes between the non-bias-corrected and seasonally corrected simulations are internally consistent, i.e. if trends in climate from a specific ESM/GCM induce similar changes in carbon pools with or without a bias correction of the forcing climate data. A large disagreement would indicate that climatic biases affect both absolute amounts of carbon as well as their change over time, which may compromise conclusions drawn from simulations forced by bias-corrected climate data.

Climate bias corrections reduce future changes in ecosystem carbon to about 60% of the changes found when not correcting for climate biases (figure 6(a)). This reduction in change is mainly attributed to a

reduction in vegetation carbon change (figure 6(b)) and to a lesser degree to climate bias impacts on soil carbon change (figure 6(c)). The reduced changes in vegetation carbon in bias-corrected simulations is likely caused by shared climate-biases between GCMs and ESMs that interact with the vegetation dynamics of LPJ-GUESS affecting biome distributions and vegetation carbon changes.

4. Discussion

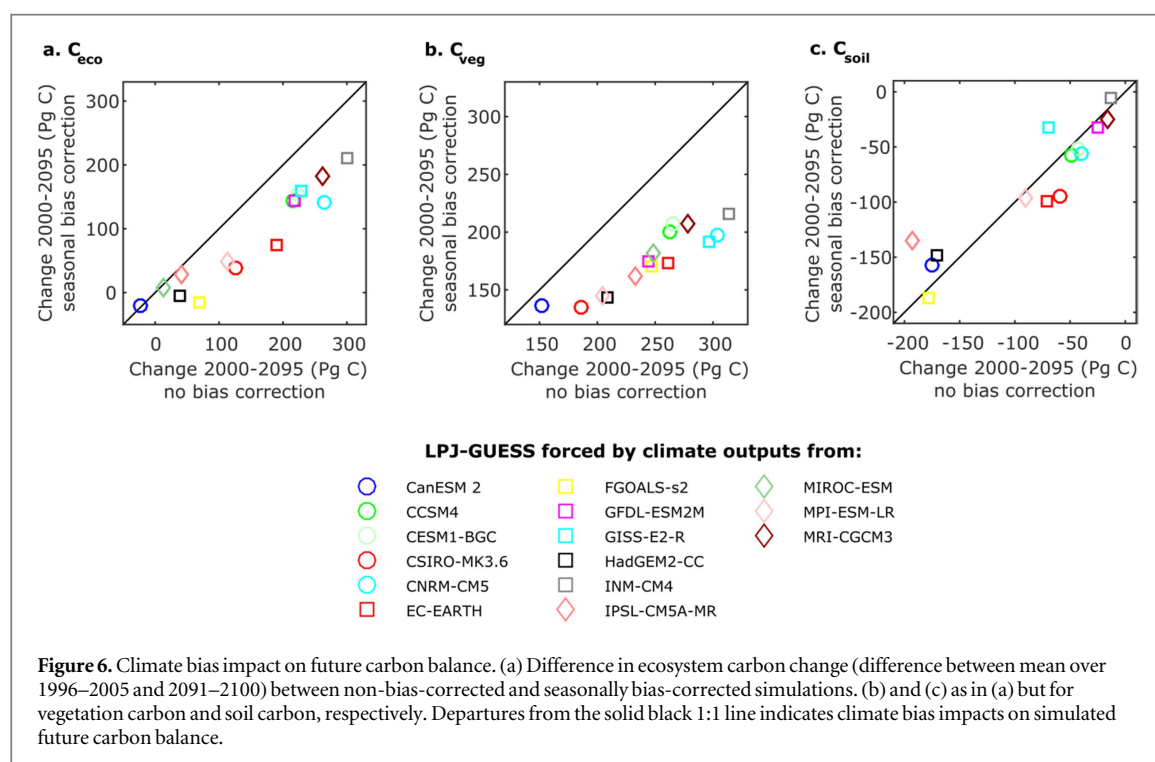
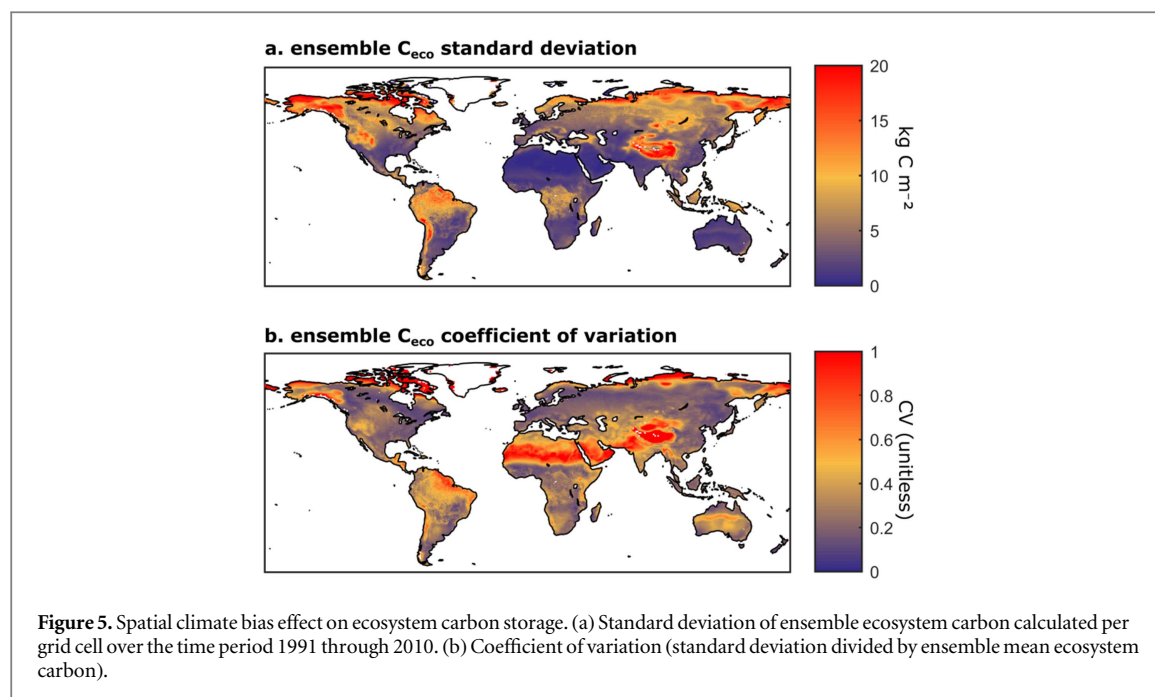
The large decrease in ensemble spread in ecosystem, vegetation and soil carbon pools after forcing our carbon cycle model with annually or seasonally bias-corrected climate implies that biases in simulated climate may explain a large proportion of uncertainties in the simulated absolute size of carbon pools among ESMs. Change fields of global total ecosystem carbon are relatively well preserved when comparing the results of bias-corrected and non-bias-corrected simulations, ESMs and GCMs resulting in large or small future changes generally do so in both bias corrected and non-bias corrected simulations (figure 6). Although bias correction significantly reduces future changes in land carbon storage (to ~60% of the changes obtained when using non-bias corrected climate), the impact of climate biases is



larger on pool sizes than on their changes in time, implying that more confidence could be ascribed to carbon pool changes from ESMs than to the absolute pool sizes. However, the global analysis presented here does not elucidate possible larger but cancelling regional impacts on trends, and previous research has shown that climate biases also affect future carbon change fields (Ahlström *et al* 2012). The carbon balance of the terrestrial biosphere is characterised by the marginal difference between much larger uptake (gross primary production) and release (respiration, biomass burning) fluxes, each with complex and regionally varying dependencies on multiple climatic drivers. Lag effects due to slow-responding vegetation

and soil processes, with time signatures from seasons to millennia, add to the complexity of the carbon balance response to climate forcing, and its apparently high sensitivity to bias in such forcing associated with climate model errors and uncertainties.

Previous research has suggested that model parameterisation of vegetation or soil processes may play an important role for carbon cycle uncertainties in ESMs (e.g. Booth *et al* 2012, Todd-Brown *et al* 2013). The analysis presented here was based on the application of a single carbon cycle model with forcing from multiple GCMs and ESMs, and focused on the effect of climate biases. We did thereby not evaluate uncertainties stemming from parameterisation or model



structure, and it remains to be confirmed whether our findings are representative to ESMs and the more generalised carbon cycle sub-models built into the majority of current ESMs. One notable relevant difference is that LPJ-GUESS simulates individual-based population dynamics where PFTs are allowed to compete for resources. This implies that the different simulations all have different distribution of PFTs and the biomes they form, with concomitant effects on simulated ecosystem functioning and carbon balance. A future shift in PFT distribution and vegetation turnover explains a part of the spread and inconsistency surrounding

carbon pool trends (Friend *et al* 2013, Ahlström *et al* 2015, Koven *et al* 2015a). On the other hand, LPJ-GUESS has been shown to be comparable to other models in terms of its sensitivity to climate variations over the historical period (Piao *et al* 2013).

The model used here does not include representations of permafrost and peatlands. Peatlands and permafrost store large amounts of carbon (Hugelius *et al* 2014) which may be increasingly lost under climate change (Koven *et al* 2015b). Carbon cycle simulations that are initialised using biased climate are less likely to capture initial carbon pool sizes, and thus, the

amount of carbon that can be lost under future warming (Todd-Brown *et al* 2014). The additional permafrost and peatland carbon would likely exacerbate this effect and the impact of climate biases on carbon storage and climate-carbon feedbacks.

Based on the results presented here, we argue that it is important to acknowledge climate bias as a potentially large source of uncertainties in ESM projections of present and future terrestrial carbon cycle processes. Conclusions drawn from raw ESM outputs on the terrestrial ecosystem should be interpreted with caution and it may be worthwhile to consider or control for the role of climate biases in future studies of ESM results.

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References

- Ahlström A, Schurgers G, Arneth A and Smith B 2012 Robustness and uncertainty in terrestrial ecosystem carbon response to CMIP5 climate change projections *Environ. Res. Lett.* **7** 044008
- Ahlström A, Smith B, Lindström J, Rummukainen M and Uvo C B 2013 GCM characteristics explain the majority of uncertainty in projected 21st century terrestrial ecosystem carbon balance *Biogeosciences* **10** 1517–28
- Ahlström A, Xia J, Arneth A, Luo Y and Smith B 2015 Importance of vegetation dynamics for future terrestrial carbon cycling *Environ. Res. Lett.* **10** 054019
- Anav A, Friedlingstein P, Kidston M, Bopp L, Ciais P, Cox P, Jones C, Jung M, Myneni R and Zhu Z 2013 Evaluating the land and ocean components of the global carbon cycle in the CMIP5 Earth system models *J. Clim.* **26** 6801–43
- Berthelot M, Friedlingstein P, Ciais P, Dufresne J-L and Monfray P 2005 How uncertainties in future climate change predictions translate into future terrestrial carbon fluxes *Glob. Change Biol.* **11** 959–70
- Booth B B B, Jones C D, Collins M, Totterdell I J, Cox P M, Sitch S, Huntingford C, Betts R A, Harris G R and Lloyd J 2012 High sensitivity of future global warming to land carbon cycle processes *Environ. Res. Lett.* **7** 024002
- Ehret U, Zehe E, Wulfmeyer V, Warrach-Sagi K and Liebert J 2012 HESS opinions 'should we apply bias correction to global and regional climate model data?' *Hydrol. Earth Syst. Sci.* **16** 3391–404
- Fisher R, McDowell N, Purves D, Moorcroft P, Sitch S, Cox P, Huntingford C, Meir P and Ian Woodward F 2010 Assessing uncertainties in a second-generation dynamic vegetation model caused by ecological scale limitations *New Phytologist* **187** 666–81
- Friend A D *et al* 2013 Carbon residence time dominates uncertainty in terrestrial vegetation responses to future climate and atmospheric CO₂ *Proc. Natl Acad. Sci.* **111** 3280–5
- Haverd V, Smith B, Nieradzik L P and Briggs P R 2014 A stand-alone tree demography and landscape structure module for Earth system models: integration with inventory data from temperate and boreal forests *Biogeosciences* **11** 4039–55
- Hempel S, Frieler K, Warszawski L, Schewe J and Piontek F 2013 A trend-preserving bias correction—the ISI-MIP approach *Earth Syst. Dyn. Discuss.* **4** 49–92
- Hickler T, Smith B, Sykes M T, Davis M B, Sugita S and Walker K 2004 Using a generalized vegetation model to simulate vegetation dynamics in northeastern USA *Ecology* **85** 519–30
- Hugelius G *et al* 2014 Estimated stocks of circumpolar permafrost carbon with quantified uncertainty ranges and identified data gaps *Biogeosciences* **11** 6573–93
- Hurt R *et al* 2011 Harmonization of land-use scenarios for the period 1500–2100: 600 years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands *Clim. Change* **109** 117–61
- Jiang L, Yan Y, Hararuk O, Mikle N, Xia J, Shi Z, Tjiputra J, Wu T and Luo Y 2015 Scale-dependent performance of CMIP5 Earth system models in simulating terrestrial vegetation carbon *J. Clim.* **28** 5217–32
- Koven C D, Chambers J Q, Georgiou K, Knox R, Negron-Juarez R, Riley W J, Arora V K, Brovkin V, Friedlingstein P and Jones C D 2015a Controls on terrestrial carbon feedbacks by productivity versus turnover in the CMIP5 Earth system models *Biogeosciences* **12** 5211–28
- Koven C D *et al* 2015b A simplified, data-constrained approach to estimate the permafrost carbon–climate feedback *Phil. Trans. R. Soc. A* **373**
- Li J L F, Waliser D E, Stephens G, Lee S, L'Ecuyer T, Kato S, Loeb N and Ma H-Y 2013 Characterizing and understanding radiation budget biases in CMIP3/CMIP5 GCMs, contemporary GCM, and reanalysis *J. Geophys. Res.: Atmos.* **118** 8166–84
- Meehl G A 2007 Global climate projections *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the 4th Assessment Report of the Intergovernmental Panel on Climate Change* ed S Solomon *et al* (Cambridge: Cambridge University Press) pp 747–845
- Mehran A, AghaKouchak A and Phillips T J 2014 Evaluation of CMIP5 continental precipitation simulations relative to satellite-based gauge-adjusted observations *J. Geophys. Res.: Atmos.* **119** 1695–707
- Mitchell T D and Jones P D 2005 An improved method of constructing a database of monthly climate observations and associated high-resolution grids *Int. J. Climatol.* **25** 693–712
- Mueller B and Seneviratne S I 2014 Systematic land climate and evapotranspiration biases in CMIP5 simulations *Geophys. Res. Lett.* **41** 128–34
- Piao S *et al* 2013 Evaluation of terrestrial carbon cycle models for their response to climate variability and to CO₂ trends *Glob. Change Biol.* **19** 2117–32
- Poulter B, Frank D C, Hodson E L and Zimmermann N E 2011 Impacts of land cover and climate data selection on understanding terrestrial carbon dynamics and the CO₂ airborne fraction *Biogeosciences* **8** 2027–36
- Purves D and Pacala S 2008 Predictive models of forest dynamics *Science* **320** 1452–3
- Riahi K, Grübler A and Nakicenovic N 2007 Scenarios of long-term socio-economic and environmental development under climate stabilization *Technol. Forecast. Soc. Change* **74** 887–935

- Schaphoff S, Lucht W, Gerten D, Sitch S, Cramer W and Prentice I 2006 Terrestrial biosphere carbon storage under alternative climate projections *Clim. Change* **74** 97–122
- Schiffer R A and Rossow W B 1983 The international satellite cloud climatology project (ISCCP): the first project of the world climate research programme *Bull. Am. Meteorol. Soc.* **64** 779–84
- Scholze M, Knorr W, Arnell N W and Prentice I C 2006 A climate-change risk analysis for world ecosystems *Proc. Natl Acad. Sci.* **103** 13116–20
- Smith B, Prentice I C and Sykes M T 2001 Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within European climate space *Glob. Ecol. Biogeogr.* **10** 621–37
- Smith B, Wårlind D, Arneth A, Hickler T, Leadley P, Siltberg J and Zaehle S 2014 Implications of incorporating N cycling and N limitations on primary production in an individual-based dynamic vegetation model *Biogeosciences* **11** 2027–54
- Taylor K E, Stouffer R J and Meehl G A 2011 An overview of CMIP5 and the experiment design *Bull. Am. Meteorol. Soc.* **93** 485–98
- Thonicke K, Venevsky S, Sitch S and Cramer W 2001 The role of fire disturbance for global vegetation dynamics: coupling fire into a dynamic global vegetation model *Glob. Ecol. Biogeogr.* **10** 661–77
- Todd-Brown K E O, Randerson J T, Post W M, Hoffman F M, Tarnocai C, Schuur E A G and Allison S D 2013 Causes of variation in soil carbon simulations from CMIP5 Earth system models and comparison with observations *Biogeosciences* **10** 1717–36
- Todd-Brown K E O *et al* 2014 Changes in soil organic carbon storage predicted by Earth system models during the 21st century *Biogeosciences* **11** 2341–56
- Trenberth K E, Dai A, van der Schrier G, Jones P D, Barichivich J, Briffa K R and Sheffield J 2014 Global warming and changes in drought *Nat. Clim. Change* **4** 17–22
- Wolf A, Ciais P, Bellassen V, Delbart N, Field C B and Berry J A 2011 Forest biomass allometry in global land surface models *Glob. Biogeochem. Cycles* **25**
- Wramneby A, Smith B, Zaehle S and Sykes M T 2008 Parameter uncertainties in the modelling of vegetation dynamics—effects on tree community structure and ecosystem functioning in European forest biomes *Ecol. Modelling* **216** 277–90
- Wu Z, Ahlström A, Smith B, Ardö J, Eklundh L, Fensholt R and Lehten V 2017 Climate data uncertainty in model based estimations of terrestrial primary productivity *Environ. Res. Lett.* in preparation
- Zhang Y, Rossow W B, Lacis A A, Oinas V and Mishchenko M I 2004 Calculation of radiative fluxes from the surface to top of atmosphere based on ISCCP and other global data sets: Refinements of the radiative transfer model and the input data *J. Geophys. Res.: Atmos.* **109**